

# Plant Litter and Soil Reflectance

# P. L. Nagler,\* C. S. T. Daughtry,† and S. N. Goward\*

T he presence of plant litter on the soil surface influences the flow of nutrients, carbon, water, and energy in terrestrial ecosystems. Quantifying plant litter cover is important for interpreting vegetated landscapes and for evaluating the effectiveness of conservation tillage practices. Current methods of measuring litter cover are subjective, requiring considerable visual judgment. Reliable and objective methods are needed. The spectral reflectance (0.4-2.5 µm) of wet and dry soils (six types) and plant litters (2 crops, 14 forest, and 2 grasses) of different ages were measured. Discrimination of plant litters from the soils was ambiguous in the visible and near-infrared (0.4–1.1µm) wavelength region. An absorption feature associated with cellulose and lignin was observed at 2.1  $\mu m$ in the spectra of dry plant litter, which was not present in the spectra of soils. A new spectral variable, cellulose absorption index (CAI), was defined using the relative depth of the reflectance spectra at 2.1 µm. CAI of dry litter was significantly greater than CAI of soils. CAI generally decreased with age of the litter. Water absorption dominated the spectral properties of both soils and plant litter and significantly reduced the CAI of the plant litters. Nevertheless, the CAI of wet litter was significantly greater then CAI of wet soil. This study provides a new methodology to discriminate plant litter from soils by differences in spectral reflectance produced by their physical and chemical attributes. This remote sensing method should improve quantification of plant litter cover and thus improve estimates of phytomass production, surface energy balance, and the effectiveness of soil conservation practices. Plant litter reflectance is a verifiable component in vegetative landscapes and should be labeled and modeled separately from soils in landscape studies. ©Elsevier Science Inc., 2000

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## INTRODUCTION

# **Ecological Importance of Litter**

Litter is senescent (or dead) plant material that gradually decomposes into soil. It is difficult to classify litter because there is no particular point in time where it shifts from one state of organic matter to another. In this study, litter is considered to be both senesced tree leaves and the portion of annual crops left in the field after harvest.

The decay of litter adds nutrients to the soil, improves soil structure and reduces soil erosion (Aase and Tanaka, 1991). The annual loss of 1.25 billion tons of soil in the United States could be reduced by leaving litter on bare soil (USDA, 1991). Litter also affects water infiltration, evaporation, porosity, and soil temperatures (Reicosky, 1994). Thus, the presence of plant litter on the soil surface influences the flow of nutrients, carbon, water, and energy in terrestrial ecosystems. Quantifying litter is important not only to improve surface energy balance, but also to improve estimates of net primary productivity and nutrient turnover rates. In agriculture systems, quantifying crop residue cover is necessary to evaluate the effectiveness of conservation tillage practices.

Crop residue can be identified and quantified using manual residue cover measurement techniques. Morrison et al. (1993) noted that the most widely used procedure to measure crop residue cover in the field (line-transect method) is tedious and prone to human judgment errors. These methods need to be replaced by more objective, faster, and more accurate spectral measurement techniques (Daughtry et al., 1996; McMurtrey et al., 1993).

#### **Spectral Properties of Litter**

Remote sensing techniques have had only limited success in quantifying litter cover because the spectral reflectance curves of plant litter and soils have similar, generally featureless shapes in the visible and near-infrared (VIS-NIR, 0.4–1.1  $\mu$ m) wavelength ranges (Aase and

<sup>\*</sup> University of Maryland

<sup>†</sup> USDA ARS Remote Sensing and Modeling Lab, Beltsville, MD Address correspondence to C.S.T. Daughtry, Remote Sensing and Modelling Lab., USDA/ARS, 10300 Baltimore Ave., Beltsville, MD 20705-2350, USA. E-mail: cdaughtry@asrr.arsusda.gov

Tanaka, 1991; Daughtry et al., 1996). The problem is that there are no unique spectral features that can be used to discriminate the similar VIS-NIR curves of plant litter and soils (Wiegand and Richardson, 1992). The slope of the reflectance spectra at the VIS-NIR transition (i.e., 680–780 nm) is generally greater for litter than for soils. However, litter may be brighter or darker than a particular soil depending on moisture conditions and litter decomposition (age), which affects the slope (Ahn et al., 1996; Daughtry et al., 1996; Goward et al., 1994).

Several studies have noted that the spectral features of dried litter and soils that are unique to each component in the shortwave infrared (SWIR, 1.1–2.5  $\mu$ m) region (Elvidge, 1990; Stoner and Baumgardner, 1981). Common spectral features in both plant litter and soils are two broad water absorption bands at 1.4  $\mu$ m and 1.9 μm. Elvidge (1990) observed diagnostic lignin and cellulose features at 2.09 and 2.3 µm in the reflectance spectra of dried plant materials. Lignin and cellulose absorptions have also been observed in Airborne Visible Infrared Imaging Spectrometer (AVIRIS) data and have been used to calculated a ligno-cellulose index based on the difference between reflectance in the 2.18  $\mu$ m to  $2.22 \ \mu \text{m}$  band and  $2.31 \text{ to } 2.38 \text{ band (Elvidge, } 1988).}$ Daughtry et al. (1996) developed a three-band spectral index for discriminating plant litter from soil that was based on the depth of the ligno-cellulose absorption feature at 2.1 relative to the shoulders at 2.0  $\mu$ m and 2.2  $\mu$ m.

Murray and Williams (1988) associated the absorption feature at 2.1  $\mu$ m with compounds possessing alcoholic -OH groups, such as sugars, starch, and cellulose. In plant litter, the absorption at 2.1  $\mu$ m is most likely due to cellulose, hemicellulose, lignin, and other structural compounds, since sugars, starches, and other non-structural compounds are readily degraded by microorganisms. The spectra of most soils show no absorption at 2.1  $\mu$ m, but rather a mineral absorption at 2.2  $\mu$ m associated with the crystal lattice of clay minerals (Stoner and Baumgardner, 1981; Ben-Dor and Banin, 1995).

#### Impact of Litter on Vegetation Indices

The spectral properties of plant litter in the VIS-NIR wavelength range affects vegetation indices, including the normalized difference vegetation index (NDVI) (van Leeuwen and Huete, 1996). NDVI values typically range from 0.08 to 0.16 for soils and 0.14 to 0.45 for litter (McMurtrey et al., 1993). The fraction of photosynthetically active radiation ( $f_{\text{APAR}}$ , 0.4–0.7  $\mu$ m) absorbed by vegetation is frequently estimated as a function of NDVI. For example, Goward and Huemmrich (1992) calculated daily total (DT)  $f_{\text{APAR}}$  as shown in Eq. (1):

DT 
$$f_{APAR} = 107.5 \cdot NDVI - 8.0$$
 (1)

If NDVI values for soils, corn residue, and forest litter from McMurtrey et al. (1993) are substituted in Eq. (1), then DT  $f_{APAR}$  ranges from 3.8% to 40.4%, even

when there no green vegetation is present. Clearly, canopy models will overestimate phytomass production unless initial surface conditions are known.

van Leeuwen and Huete (1996) found the effect of different vegetation components on the soil adjusted vegetation index (SAVI) was higher for litter and bark canopies than for bare soil, as shown when computed from the SAIL model. They cite the litter/bark scattering properties at the leaf scale as a potential cause of the error in the VI response to green vegetation cover. Distinction between soils can be further demonstrated by differences in slope when cross-plots of their NIR-red reflectance are employed (Huete et al., 1985). Furthermore, variations in VI can be seen if these cross-plots are shown for both plant litter and soils.

The influence of plant litter reflectance has generally not been recognized in canopy spectral measurements (Goward and Huemmrich, 1992). As a result, the spectral reflectance of dry, bare soil rather than plant litter (e.g., Myneni et al., 1995) is used to monitor landscape processes because soil is a more permanent ground component than litter. Thus, the impact of plant litter is often neglected in spectral models that estimate plant productivity. Until plant models can account for energy that is not used to produce dry matter, such as energy absorbed by litter and by soils, these models cannot be used to accurately predict plant productivity or even the physiological state of plant canopies. Canopy models, which include green vegetation, plant litter, and soil optical properties, are more likely to evaluate the condition and yield of vegetation correctly (Daughtry et al., 1992).

The objectives of this work were to (1) acquire and analyze spectral reflectance data for a wide range of soils and plant litters and (2) develop an algorithm for discriminating litter from soil.

### MATERIALS AND METHODS

#### Plant Litter and Soils

Coniferous needles and deciduous broadleaf litter were collected on four dates, representing litter aged 1, 8, 12, and >12 months after senescence (MAS) from 14 tree stands [i.e., six Pine (*Pinus*), one Hemlock (*Liquidambar*), two White Oaks (*Quercus*), two Sweetgum (*Tsuga*), and three mixtures of predominant canopies of Maple (*Acer*), Poplar (*Populus*), and Sassafras (*Sassafras*)].

Corn (Zea mays L.) and soybean (Glycine max (L.) Merr.] residues were collected from agricultural fields at <1, 6, 8, and 10 months after harvest (MAH). Two grasses (Poa pratensis L. and Festuca arundinacea Schreb.) were collected to represent three ages, 6 (April), 8 (June), and 10 (September) MAS. All plant litter samples were dried at 70°C and stored at room temperature until spectral measurements could be made.

Six U.S. cropland soils (i.e., Barnes, Codorus, Othello,

		Family/Subgroup	Munsell Color		
Series	Order	Classification	Wet	Dry	
Cecil	Ultisol	Clayey-kaolinitic	Reddish brown	Strong brown	
		Thermic Typic Hapludult	5 YR 5/4	7.5 YR 5/6	
Othello	Ultisol	Fine silty, mixed, mesic	Dark grayish brown	Light brownish gray	
		Typic Ochraquult	10 YR 4/2	10 YR 6/2	
Codorus	Inceptisol	Fine loamy, mixed, mesic	Dark brown	Light yellowish brown	
		Fluvaquentic Dystrochrept	7.5 YR 3/2	2.54 YR 6/4	
Portneuf	Aridisol	Coarse loamy, mixed, mesic	Very dark grayish brown	Brown	
		Durixerollic Calciorthid	10 YR 3/2	10 YR 5/3	
Barnes	Mollisol	Coarse loamy, mixed	Black	Very dark grayish	
		Udic Haploboroll	10 YR 2/1	10 YR 3/2	
Houston	Vertisol	Fine, montmorillonitic	Very dark gray	Very dark gray	
Black Clay		Thermic Udic Pellustert	5 YR 2.5/1	5 YR 3/1	

Table 1. Soils Sample Description by Classification of Series, Order, Family, Subgroup, and Munsell Color Wet and Dry

Portneuf, Cecil, Houston Black Clay), representing a range of colors and textures, were used in this study (Table 1). Each soil sample was dried at 70°C and crushed to pass a 2-mm screen.

#### **Reflectance Measurements**

Bidirectional spectral reflectance data over the  $0.4 \mu m$  to  $2.5 \mu m$  wavelength region were acquired with an IRIS Mark IV spectroradiometer (Geophysical Environmental Research, Corp., Millbrook, NY, USA). Note that company and trade names are given for the benefit of the reader and do not imply any endorsement of the product or company. The spectrometer used two detectors, one in the VIS-NIR (0.4–1.1  $\mu$ m) and one in the SWIR (1.1–  $2.5 \mu m$ ), and readings were collected every 2 nm in the VIS-NIR and every 4 nm in the SWIR. Although the spectroradiometer had dual 2×6° fields of view, it was operated as a single beam instrument (i.e., both sample and reference channels viewed different areas of the same target). The spectroradiometer was positioned at a zenith view angle of 30°, resulting in views of two areas approximately 2×7 cm each. An external light source illuminated the samples using 16 62-W quartz-halogen lamps reflecting from a hemisphere painted with BaSO<sub>4</sub> (Williams and Wood, 1987). The hemisphere provided nearly uniform illumination over an area larger than the field of view of the spectroradiometer.

Black-painted sample trays (45×45×2.5 cm) were filled with dry litter or soil. Nine pairs of spectral data were acquired at different locations on each sample. Reflectance factors were calculated according to the methods described by Biehl and Robinson (1983), where the samples and a white Spectralon panel (30×30 cm) (Labsphere, Inc., North Sutton, NH, USA) were measured under the same illumination and observation conditions. Specifically, reflectance factor is the sample reading divided by the reference panel reading and multiplied by the absolute reflectance of the panel.

After the spectral reflectance of the dry samples was

measured, the litter samples were immersed in water for at least 2 hours, drained, and then measured again. Soils samples were saturated with water and allowed to drain overnight before acquiring spectral data for wet samples.

Reflectance factors (R) were plotted as a function of wavelength. Two minor discontinuities in the spectra (centered at 1.1  $\mu$ m and at 1.8  $\mu$ m) were associated with a change in detectors and/or change in the diffraction gratings. Statistical analysis system (SAS Institute Inc., Cary, NC, USA) mixed models procedure was used to test for significant differences associated with moisture and age of litter.

# NDVI of Litter and Soils and Their Impact on Estimates of $f_{APAR}$

NDVI values for crop residues, forest litter, and soils samples were calculated and the effects of different ground components on the  $f_{APAR}/NDVI$  relationship were evaluated. The mean NDVI values were used to estimate productivity (without considering radiative transfer and canopy reflectance) with a linear equation for the slope and intercept of the relationship between  $f_{APAR}$  and NDVI (Daughtry et al., 1992; Goward and Huemmrich, 1992). The effects of soil and plant litter reflectance on estimates of  $f_{APAR}$  were determined by simulating canopy reflectance and NDVI using the SAIL model (Verhoef, 1984) for a wide range of LAI values (0.01, 0.25, 0.50, 0.75, 1.0, 1.5, 2.0, 3.0, and 4.0). Estimates from the linear equation and the SAIL model were comparable.

#### RESULTS AND DISCUSSION

#### **VIS-NIR** Wavelengths

Mean VIS-NIR reflectance spectra of dry (dashed lines) and wet (solid lines) soils and litter types are shown in Fig. 1. The spectral behavior of the soils and plant litter were similar in the VIS-NIR wavebands, generally featureless as Aase and Tanaka (1991) described, and indistinguishable due to the variability of the individual com-

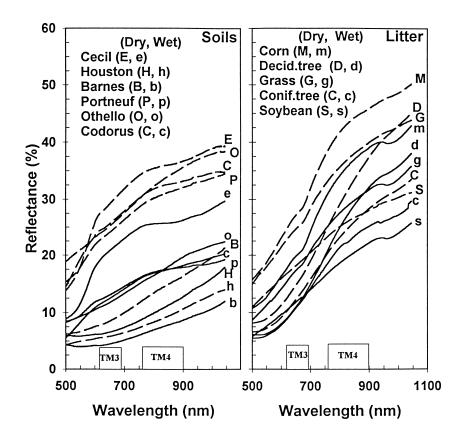


Figure 1. VIS-NIR spectral reflectance (0.5–1.1  $\mu$ m) of dry (dashed lines) and wet (solid lines) soils and litter types.

ponents. The two Thematic Mapper (TM) bands (TM3, 0.63–0.69  $\mu$ m; TM4, 0.76–0.90  $\mu$ m) that are used to calculate NDVI are also indicated in Fig. 1.

Soil color is easily detectable, often related to soil properties, and useful in identifying and classifying soils in the visible (0.4–0.7  $\mu$ m) spectral range (Cloutis, 1996; Escadafal et al., 1989). Bright soils had the highest reflectance and dark soils had the lower reflectance throughout the spectral range. Houston Black Clay was such a very dark gray that it hardly changed color as it dried; it had nearly the same reflectance both wet and dry. For the other soils, the reflectance of the wet soil was approximately one-half the reflectance of the dry soil.

Many studies have been done on soil reflectance patterns, but few quantitatively related spectral shape to soil properties. Generally, soils rich in organic carbon have concave reflectance curves between 0.5  $\mu$ m and 1.3  $\mu$ m, whereas soils low in organic carbon have convex reflectance curves (Huete and Escadafal, 1991). Although none of the spectra showed unique absorption features, five of the dry soils curves appeared convex while only the dry Barnes and dry Houston Black Clay were concave; three of the wet soil curves also appeared concave (i.e., Houston Black Clay, Barnes, and Portneuf). These mineral soils curves are consistent with the results of Stoner and Baumgardner (1981) who described five general soil reflectance shapes.

For litter samples, the concavity of the spectra was slightly different among grasses, crop residues, and tree litter. The shape of the tree litter spectrum was more sigmoidal than soils. The number of inflection points was different for each type of litter component (i.e., lowest in soybean to highest in deciduous litter) and produced a range in NDVI values from soybean (lowest), to corn, coniferous, then deciduous forest litter (highest). Nevertheless, the various litters had reflectance spectra that were generally indistinguishable in the VIS-NIR.

The primary difference between the soils and litter reflectance spectra in the VIS-NIR wavelengths was that the slopes of all the litter spectra were slightly greater than the soils. Figure 2 is a plot of the NIR reflectance as a function of VIS reflectance of the litter and soil samples. The wet and dry soil samples lie close to the regression line (soil line). Reflectance of the plant litter samples were quite variable as indicated by the large error bars that represent  $\pm 1$  standard deviation of the mean. Thus, discriminating plant litter from soil is difficult for some combinations.

The soybean samples are closest to the soil line, resembling the soils in spectral reflectance more than the other litter types. Deciduous tree litter is the furthest from the soil line, followed by the senescent grasses, coniferous litter, and corn. From Huete et al. (1985), the driest samples on the soil line have the highest reflectance in both TM3 and TM4, whereas the wettest soils have the lowest reflectance in both bands. The samples furthest from the soil line are the most similar to green vegetation. Directional deviations from the soil line show

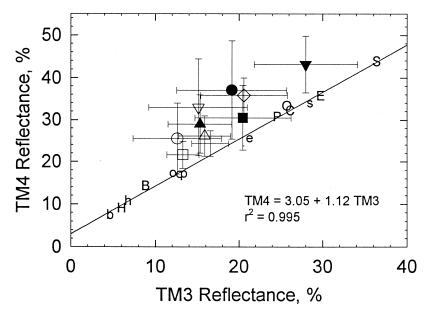


Figure 2. Plot of the NIR (TM4: 760-900 nm) reflectance as a function of VIS (TM3: 630-690 nm) reflectance of the soils and litters. The soils are: Othello (O, o), Cecil (E, e), Codorus (C, c), Portneuf (P, p), Barnes (B, b), Houston Black Clay (H, h), and beach sand (S, s). The regression line fits the soils data. For the plant litters, the hollow symbols represent the dry samples and the solid symbols represent the wet samples. The error bars are ±1 standard deviation of the mean.

color biases (i.e., toward red, yellow, etc.) and distance deviations show color intensity. Reflectance spectra of organic soils are more variable than the spectra of mineral soils (Stoner and Baumgardner, 1981).

Figure 3 describes the effect of background reflectance on estimates of  $f_{APAR}$  as a function of NDVI using the SAIL model (Verhoef, 1984). The mean reflectance of soils, crop residues, and forest litter at two moisture levels was determined. Values of NDVI ranged from 0.09 for dry soil to 0.30 for wet forest litter. The  $f_{APAR}$  can be over- or underestimated if the ground component is not

properly identified. For example, if one assumes that the scene background is dry soil when the true background is wet forest litter, then  $f_{APAR}$  would be overestimated by approximately 0.20 units. The effects of this error are compounded as other models use  $f_{APAR}$  to estimate phytomass production, evapotranspiration, surface energy balance, etc. The greater the difference between component types, the larger the error in the  $f_{APAR}$  estimates. Thus, it is crucial to correctly identify background com-

In many ecosystems, standing plant litter partially

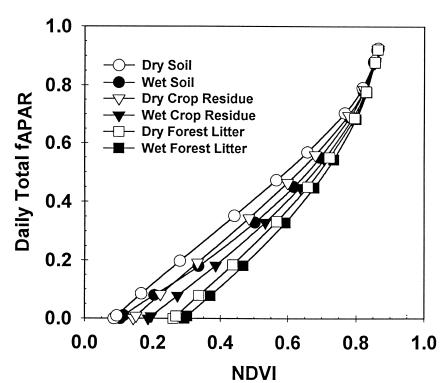


Figure 3. Effect of dry and wet soils, crop residues, and forest litter on the  $f_{APAR}$ NDVI relationship.

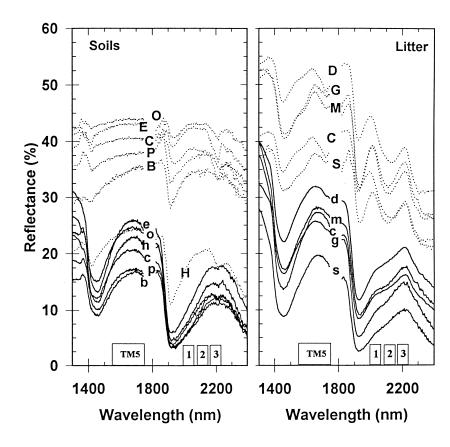


Figure 4. SWIR spectral reflectance (1.3-2.4  $\mu$ m) of dry (dashed lines) and wet (solid lines) soils and litters. The soils are: Othello (O, o), Cecil (E, e), Codorus (C, c), Portneuf (P, p), Barnes (B, b), and Houston Black Clay (H, h). The plant litters are: corn (M, m), soybean (S, s), deciduous tree (D, d), coniferous tree (C, c), and grass (G, g).

obscures green vegetation early in the growing season and during senescence. Models with only two classes of scene components (i.e., green vegetation and nongreen materials), are inadequate. At least three classes of scene components (i.e., green vegetation, plant litter, and soil) are required for canopy models to accurately describe surface conditions.

#### SWIR Wavelengths

Mean SWIR reflectance spectra from six soils and five litter types are shown in Fig. 4. The dominant features are two water absorption bands, centered at 1.4  $\mu$ m and 1.9  $\mu$ m. Also evident in the spectra of the dry litter is a broad absorption band at 2.1  $\mu$ m that is associated with cellulose and lignin (Murray and Williams, 1988; Elvidge, 1990). The mean spectral reflectance in the bands centered at 2.0  $\mu$ m, 2.1  $\mu$ m, and 2.2  $\mu$ m could be used to measure the concavity or depth of the cellulose-lignin absorption feature. These three bands, plus the Landsat TM band centered at 1.65  $\mu$ m, are shown in Fig. 4. Other bands are not shown because the differences at other wavelengths, between the spectra of soils and litter, were smaller. Water in the samples significantly altered the reflectance spectra of both soils and litter (Fig. 4). First, moisture reduced overall reflectance at all wavelengths in each sample. Second, the water absorption bands at 1.4  $\mu$ m and 1.9  $\mu$ m broadened and the wings of the 1.9  $\mu$ m band nearly obscured the celluloselignin absorption at 2.1  $\mu$ m. The altered shape of the wet litter reflectance spectra initially appeared very similar to the wet soil spectra. However, the slight concavity of the cellulose-lignin absorption remained. Gao and Goetz (1994) examined subtle shape changes in reflectance spectra of water and green leaves and concluded that absorption features of the plant material could be identified even in spectra dominated by water.

Since the cellulose-lignin absorption feature at 2.1  $\mu$ m is relatively broad and appears to shift slightly from sample to sample, we selected the three 0.04 µm-wide bands indicated in Fig. 4. Several indices of these SWIR bands were explored including simple two-band ratios and indices, much like NDVI. However, the best combination for discriminating plant litter from soils was with a three-band index called cellulose absorption index (CAI), which was defined by the relative depth of the spectral absorption at 2.1  $\mu$ m. Mean spectral reflectance from each sample for each band was used to calculate CAI as shown in Eq. (2):

$$CAI = 0.5 (R_{2.0} + R_{2.2}) - R_{2.1}$$
 (2)

where  $R_{2.0}$ ,  $R_{2.1}$ , and  $R_{2.2}$  are the wavebands centered at  $2.02~\mu\mathrm{m}$ ,  $2.10~\mu\mathrm{m}$ , and  $2.22~\mu\mathrm{m}$ , respectively.

In Fig. 5, CAI was plotted as a function of sample moisture content, which can be monitored by reflectance in the water absorption band (1.9  $\mu$ m) (Murray and Williams, 1988). Wet samples (litter and soils) had reflectances that were <25% (all wet soils were <10%), while dry samples were generally >25%, with the exception of

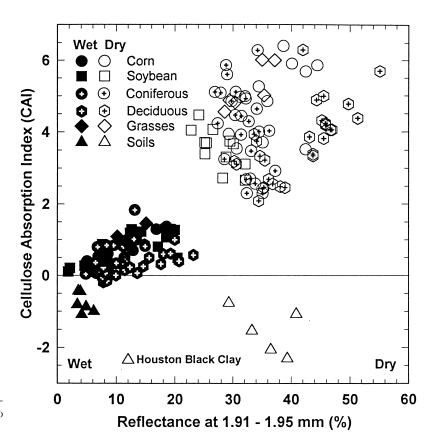


Figure 5. Plot of the CAI as a function of reflectance in a water absorption band at 1.91  $\mu m$  to  $1.95 \ \mu m.$ 

Houston Black Clay (11% water), which held more moisture when air-dried than other soils. The presence of water reduced the reflectance of all samples at all wavelengths and made discrimination of litter and soils difficult.

Although water absorption dominated the spectral properties of both soils and residues in the SWIR, it was possible to discriminate wet litter from wet soil using CAI. More than 90% of the wet plant litter samples had

positive CAI values. However, CAI values were slightly negative for three wet deciduous samples and two coniferous samples that were all greater than 1 year old. These five samples were sufficiently decomposed so that the absorption due to cellulose and/or lignin fibers was easily masked by moisture.

In practice, the targets will be mixtures of soil and litter and the effect of moisture will be more significant for scenes with small fractions of litter cover. Daughtry

Table 2. Effect of Age of Litter and Moisture Content on CAI of Crop Litter

		CAI					
Type	n	1 month	5 months	7 months	10 months	Mean	
Corn	3	5.77	4.15	4.61	5.03	4.89a	
Soy	3	4.08	3.73	3.58	2.84	3.56b	
Grass	2	_	5.42	4.95	5.29	4.88a	
Soils	7	_	-	-	-1.58	-1.58c	
				Wet			
Type	n	1 month	5 months	7 months	10 months	Mean	
Corn	3	0.84	0.92	0.84	1.01	0.90d	
Soy	3	0.79	0.85	0.72	0.86	0.80de	
Grass	2	_	0.71	0.62	1.03	0.66de	
Soils	7	_	_	_	-0.72	-0.72f	
			SED:	SI	ED = 0.16		

The number of observations in the crop residue mean is 3 and for grass it is 2. A conservative standard error difference (SED  $t_{0.05}$ ) was calculated using  $n\!=\!2$  to make comparisons between types and ages. Means followed by the same letter are not significantly different at the  $t_{.05}$  level. A conservative SED with n=6 is listed for comparisons between means.

			CAI			
	Dry					
Туре	1 month	8 months	12 months	12 months	Mean	
Coniferous	5.25	4.24	3.90	2.61	4.06a	
Deciduous	4.84	3.92	3.70	2.59	3.77	
Soils	=	=	=	-1.58	-1.58	
			Wet			
Туре	1 month	8 months	12 months	12 months	Mean	
Coniferous	0.83	0.46	0.59	0.09	0.500	
Deciduous	0.44	0.35	0.20	0.03	0.26	
Soils	_	_	_	-0.72	-0.721	
		SED=0.38 SI			ED = 0.10	

Table 3. Effect of Age of Litter and Moisture Content on the CAI of Tree Litter

The number of observations in the tree litter means (for each age) varies between five and seven. The most conservative standard error difference (SED  $t_{0.05}$ ) is listed at the bottom of the table to make comparisons between types and ages. Means followed by the same letter are not significantly different at the  $t_{.05}$  level. The most conservative SED is listed for comparisons between means.

et al. (1996) simulated mixed spectra and determined that a 0.1 change in the fraction of cover for dry litters and soils would produce significant differences in CAI; however, for wet mixed spectra, a narrow range of CAI values would make discrimination difficult. Nagler et al. (1998) measured reflectance of mixed (litter+soil) scenes and found that CAI increased linearly as plant litter cover increased. Mixed scenes with more than 10% litter cover had CAI values that were significantly larger than the CAI values of bare soils. Mixture modeling for soil-litter scenes needs to be explored.

Harmonic mean comparisons, which allow sample pairs with different numbers of repetitions to be compared, showed that significant differences in CAI exist due to moisture, litter type, and litter age (Tables 2 and 3). Moisture significantly reduced CAI in each litter. Mean CAI of dry litter tended to decrease with age, presumably as a result of cellulose and/or lignin decomposition (Elvidge, 1990).

The changes in reflectance due to sample moisture were so dominant that CAI did not show a significant change with age for any of the wet samples. Nevertheless, the CAI values of all plant litters, regardless of moisture content, were significantly greater than CAI values of the soils.

#### **CONCLUSIONS**

Our results support earlier findings that it is difficult to reliably distinguish plant litter from soils using reflectance spectra in the VIS-NIR wavelength region because plant litter may be brighter or darker than the soil. Plant litter can be discriminated from soils using the celluloselignin absorption feature in the SWIR wavelengths. Further research is required to evaluate the effects of green

vegetation and mixed (soil+litter) scenes on the discrimination of plant litter from soils. Additional work is also needed to evaluate new sensor systems with narrow band widths in the SWIR region.

The value of this SWIR remote sensing method to estimate the litter cover must be evaluated in natural canopies or agricultural lands. Work to test this methodology in agricultural fields is underway. If successful, CAI may replace the current manual methods of quantifying plant litter cover.

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